Endogenous Technology and Local Labor Market Skill[*]

Nicole Nestoriak[†]
University of Maryland
October 2003

[*] We would like to acknowledge the substantial contributions of members of the LEHD staff in preparing the data used in this document. This document reports the results of research and analysis undertaken by the U.S. Census Bureau staff. It has undergone a Census Bureau review more limited in scope than that given to official Census Bureau publications. This research is a part of the U.S. Census Bureau's Longitudinal Employer-Household Dynamics Program (LEHD), which is partially supported by the National Science Foundation Grant SES-9978093 to Cornell University (Cornell Institute for Social and Economic Research), the National Institute on Aging Grant 5 R01 AG018854-02, and the Alfred P. Sloan Foundation. The views expressed herein are attributable only to the author(s) and do not represent the views of the U.S. Census Bureau, its program sponsors or data providers. Some or all of the data used in this paper are confidential data from the LEHD Program. The U.S. Census Bureau is preparing to support external researchers' use of these data; please contact U.S. Census Bureau, LEHD Program, Demographic Surveys Division, FOB 3, Room 2138, 4700 Silver Hill Rd., Suitland, MD 20233, USA.
[†] I am grateful to John Haltiwanger, John Abowd, Judy Hellerstein, Hyowook Chiang, Kevin Moore, Kristin Sandusky and members of the LEHD program staff for helpful comments and advice

Abstract

Despite the focus on the effects of new technologies and highly skilled workers in contributing to economic growth and explaining increasing wage inequality, the use of these new technologies and workers is not necessarily widespread. In fact, if one looks at firm level data, it becomes clear that while some firms do appear to be utilizing the latest technologies and most highly skilled workforces, there are also many firms that have not adopted the latest technologies and that have de-skilled their workforce. What is generating this heterogeneity? This paper proposes one answer: there is considerable geographic variation in the availability of skilled workers, and this variation in conjunction with labor market frictions forces firms to consider the skill mix of their local labor market before making an investment decision, thereby leading to endogenous technology.

While previous studies of this phenomenon have focused on macro-level changes in the relative supply and demand of skilled labor, this paper utilizes cross-sectional variation in the availability of skilled labor in local labor markets to determine if otherwise similar firms invest differently in high technology capital depending upon the locally available skill mix. Employer-employee matched data is used to examine the relationship between an establishment's investment in high technology and local labor market skill while controlling for the firm's skill mix, industry and type. The results predict that a one standard deviation increase in local labor market skill will lead to a 10 to 20% increase in technology investment, holding other characteristics of the firm constant. These results are robust to a series of different specifications including different measures of local labor market skill and definitions of the local labor market.

Despite the focus on the effect of new technologies and highly skilled workers on the economy, the use of these new technologies and workers is not necessarily widespread. In fact, if one looks at firm level data, it becomes clear that while many firms do appear to be utilizing the latest technologies and most highly skilled workforces, there are also many firms who have not adopted the latest technologies and who have in some sense de-skilled their workforce. While the overall trends, particularly in the 1980s, seemed to be in favor of using more educated workers, there is heterogeneity behind that trend. If the new way of doing business is vastly superior, why are there businesses outside of the trend? This paper proposes one answer: the highly skilled workforce necessary to implement the latest technologies is an input into production that is very different from capital or materials. The fact that labor is a unique input that leads to endogenous technology is not a new idea in the economics literature.[1] However, while previous studies of this phenomenon have focused on macro-level changes in the relative supply and demand of skilled labor, this paper utilizes variation in the availability of skilled labor across local labor markets to determine if otherwise similar firms invest differently in high technology capital depending upon the locally available skill mix.

The cause of this form of endogenous technology lies in the timing of the firm's investment decision. Because firms must often decide how they would like to conduct their business before they know whom they may be able to hire, they must make their investment decisions based on the type of worker that they expect to be able to hire. Workers, while mobile, tend to locate near other similar workers thereby limiting the ability of a firm in a low skill area to attract a high skill workforce. Firms who attempt to recruit more skilled workers potentially face large search costs both in recruiting workers and in the cost of having capital lay idle. If a particular type of worker is scarce in the local labor force, the firm will be forced to devote more resources in finding that type of worker and risk a longer period before a vacancy is filled. These forces imply that firms must consider the composition of their local labor market before making capital investments and posting vacancies. In particular, the question asked here is, do firms consider the skill mix of the local labor market before making a technology investment decision?

The model constructed captures these ideas and provides a framework for the later empirical work. The model is a two-period matching model based on Acemoglu (1996). In the first period, firms know the distribution of workers in their local labor market, but not the worker with which they will match. Based on this information and their knowledge of their firm type, firms make an investment decision. Worker skill is predetermined in the model. In the second period, workers and firms meet and production takes place. This model sets up the two key equations for estimation: a wage equation and an investment equation. The wage equation takes advantage of a large data set and helps to quantify worker and firm heterogeneity. The investment equation uses results from the wage equation in combination with other firm data to directly address the questions laid out above.

The data requirements to empirically study this question are significant. Not only does one need detailed establishment information including the firm type, and the amount and type of investment, but also it is necessary to know where the business is located. On the worker side, one must know the skill level of all employees in a local labor market and, ideally, the skill level at each establishment. A newly developed linked employer-employee data set available at the Census Bureau makes this research possible. State level universe files containing all employers and employees allow one to decompose wages into an explained component due to worker experience and labor force attachment, a worker heterogeneity term, and a firm heterogeneity term. This in combination with links to the Economic Censuses, which provide information on establishment level investment, make it possible to answer the question set out earlier. Estimates of the effect of endogenous technology predict that a one standard deviation increase in local labor market skill will lead to a 10 to 20% increase in technology investment. These results are robust to a series of different specifications including different measures of investment, local labor market skill, and definitions of the local labor market.

Endogenous Technology

In the late 1970s, the United States saw a large increase in the relative number of college graduates. Traditional factor-demand analysis would suggest that this would be followed by a

---

[1] See Acemoglu (1998), Kiley (1999), Albrecht and Vroman (2001).

decrease in the relative wage of skilled workers. On the contrary, throughout the 1980s there was an increase in the price paid for college educated workers. Researchers studying the increased wages paid to more skilled workers have considered many possible explanations including shifts in demand, the effects of trade, and the skill bias of new technologies. Focusing here on the later of the possible explanations, the use of skill biased technology increased the demand for skilled workers faster than the supply of skilled workers was growing, thereby leading to a rise in wages to highly skilled workers while their numbers where also increasing.

The endogenous technology theory provides a link between these two events. In reaction to the increase in the availability of more skilled workers, businesses began investing more in technologies to utilize this newly available human capital. Models have incorporated this endogenous technology choice in different ways. Acemoglu (1998) and Kiley (1999) set up models in which the economy has two sectors, research and production. The research sector chooses to develop the technologies that will command a high price and that will be demanded by a large number of firms in the production sector. The increase in the availability of skilled workers in the late 1970s, therefore, increased the number of production firms that could potentially use skill-biased technology. The research sector's incentives shifted as the supply of skilled workers increased. As more skill-biased technologies became available, more production firms utilized these technologies, and simultaneously demanded more skilled workers.

A similar set of models, Acemoglu (1999), Albrecht and Vroman (2002), Eudey and Molico (2001), relies on the fact that firms must commit to a type of investment before meeting workers. Each of the above papers assumes that there are two types of vacancies defined by their technology and two types of workers defined by skill. Firms decide which type of vacancy to create by determining the probability of meeting a worker appropriate to that technology. The types of vacancies created by firms critically depend upon the skill mix of the workforce. A workforce with a mix of high skill and low skill workers leads to a pooling equilibrium in which only one type of vacancy is created, while a workforce with a greater proportion of skilled workers will lead to a separating equilibrium with some vacancies specifically created for high skill workers. These papers then study the effects these different equilibriums have on either wage inequality or productivity within the economy. A similar model with a continuum of vacancies, defined by amount of technology investment, is developed below.

Firm Heterogeneity

Beyond the previous theoretical research on endogenous technology, there is also a fair amount of empirical evidence that firms do exercise a choice in the type of technology that they use. Haltiwanger, Lane and Spletzer (2000), using a similar data set to that used here, look at worker characteristics within firms over time. They find considerable heterogeneity across firms in their choice of worker mix even after controlling for detailed industry and other observable firm characteristics. In addition, these firm differences persist over time, suggesting that they are the result of a firm choice and not merely the result of error on the part of the firm or noise in the data. Abowd, Haltiwanger, Lane, and Sandusky (2001), again using similar data, look at the connections between worker characteristics and firm characteristics. In their analysis of Illinois over the 1990s, they find in a cross sectional analysis that firms with greater levels of technology also have more skilled workforces, and that over time firms that increase their use of technology also increase their use of skilled workers.

Bresnahan, Brynjolfsson and Hitt (2002) look jointly at worker skill, workplace organization, and technology investment. In their work, they find that firms that invest heavily in information technology not only have more highly skilled workforces, but additionally they have less centralized workplace organizations. The combination of all three of these factors suggests that a firm deciding to invest in high technology must also be willing to invest heavily in changing its workforce to fully take advantage of the new technology. Among their most interesting results, as it pertains to the research set out here, is a regression of log output on labor, capital and a series of four dummies: firms with both high technology and high worker skill, high technology but low worker skill, low technology and high worker skill, and finally low technology and low worker skill. Not surprisingly, the dummy for the high-high mix was large and positive. However, the low-low combination represented the next largest coefficient. These results provide further evidence that firms have a viable alternative to doing business using the latest high technology. Furthermore, a combination of workers and capital that complements each other has higher productivity than either using new technology or highly skilled workers singly.

In addition to the cross-sectional heterogeneity in technology usage mentioned above, the time-series variation in relative technology-skill complementarity highlights the point that it is not necessarily optimal for all firms to be using a high skill/high technology mix. Goldin and Katz (1998) examine the evolution of technology-skill complementarity and find that while more recent advances in technology have been skill biased, new technologies adapted in the 19th century were in fact biased toward unskilled labor. The shift from the artisanal shops to factories using assembly lines may have been an advance in technology, but it certainly involved a reduction in the amount of skilled labor required. They argue that, although skilled labor and capital are complements within the implementation and maintenance of a given technology, they may be complements or substitutes among different technologies.

Local Labor Market

Finally, a couple of papers study different aspects of the relationship between local labor market characteristics and firm characteristics. Moretti (2002) estimates establishment production functions including the change in the college share outside of the establishment's industry to identify the extent of human capital spillovers. In order to control for various unobservable factors that might influence both establishment productivity and the share of college graduates in their local labor market, Moretti controls for plant, industry by year, and state by year fixed effects. Therefore, identification of the human capital spillovers comes from changes in the college share variable correlated with changes in productivity for establishments that survive from 1982 to 1992. Moretti finds that human capital spillovers are responsible for a 0.1% increase in output per year during the 1980s. The key difference between Moretti's model and the one outlined here is that in Moretti's model it is assumed that firms and workers are perfectly mobile. Variation in the amount of human capital spillovers across areas continues to exist in equilibrium due to variation in the price of the untraded good, land. In the model below, variation across local labor markets is driven by the limited mobility of workers and establishments.

Fallick, Fleischman, and Rebitzer (2003) study the relationship between local labor market worker mobility and characteristics of agglomeration economies and of Silicon Valley in particular. They note that one key aspect of Silicon Valley that makes it different than other agglomeration economies is the existence of a California law that makes it impossible for employers to enforce non-compete agreements. This law in combination with the modularity of technology being developed in Silicon Valley has led to knowledge spillovers via unusually high mobility of workers between establishments. Their results suggest that Silicon Valley may be a special case of endogenous technology due to the exceptionally common transfer of employees between firms.

The Model

The endogenous technology model developed here is a two period matching model similar to one in Acemoglu (1996). While Acemoglu focuses on social increasing returns to human capital, the search frictions in the labor market within his model can also be shown to lead to endogenous technology. Within the model developed here, the economy consists of a single autonomous local labor market and exists for two periods. While a full model of this economy would include multiple local labor markets and would allow for endogenous worker and firm mobility, here the larger economy can be thought of consisting of many local labor markets operating independently of one another. Workers vary in their skill level and are exogenously distributed across local labor markets. An individual worker's skill level is determined outside the model. Intuitively, this suggests that worker's cannot adjust their skill level within the time frame of a firm choosing it's investment level, i.e. a worker with a high school degree cannot obtain a college degree in the time that a firm requires to choose and implement new technology. For simplicity in exposition, there are only two types of worker skill in the model, a high skill level and a low skill level. Extending the model to a continuum of skill types would not affect any of the important results of the model. Firms vary in their predetermined type and in the amount of their capital investment. There is a fixed marginal cost of capital equal to μ.

The basic timing of the model is as follows. In period one, firms observe the distribution of workers in their local labor market, but do not know the type of worker with which they will match. The firm decides on a level of capital investment. In the second period, firms and workers are randomly matched to each other. Firms and workers must decide whether to continue with the match and produce or to remain idle for the period. Search costs create quasi-rents for the firm and worker within the match. If production takes place, returns to workers and firms are determined via a Nash bargaining solution. Workers receive a fraction B of match surplus and firms receive 1-B. Match surplus is equivalent to output in this model because the firm's first period investment is a sunk cost. Both workers and firms have zero opportunity cost, and it is assumed that output is nonnegative, therefore workers and firms will accept any division of match surplus and production will occur with all matches. Within this model, the Nash bargaining solution can be shown to be a general solution. The specific case in which B is equal to α, labor's share of income under constant returns to scale and Cobb-Douglas production, is equivalent to assuming that factors receive their marginal product.

Production takes place in worker/firm pairs

$$Y_{ij} = A_j h_i^{\alpha} k_j^{1-\alpha} \tag{1}$$

where α is a value between 0 and 1, h_i is worker type i's human capital, k_j is firm j's capital investment, and A_j is firm j's idiosyncratic term meant to capture firm type, i.e. managerial ability, corporate culture, etc. Worker type i is equal to either 1 or 2, low skill level and high skill level respectively. As mentioned earlier, a fraction ρ of workers are type 2.

In the second period, the realized returns for a worker i and firm j are

$$W(h_i, k_j) = B\ A_j h_i^{\alpha} k_j^{1-\alpha} \tag{2}$$

$$R(h_i, k_j) = (1-B) A_j h_i^{\alpha} k_j^{1-\alpha} \tag{3}$$

As laid out above, workers and firms receive share B and 1-B of the match surplus. In the first period, firms and workers know the distribution of worker and firm types. Therefore, under rational expectations, workers' and firms' expectations of their second period earnings are the expected value of the ex-post earnings.

$$W(h_i, \{k_j\}) = B\ h_i^{\alpha} (\int A_j k_j^{1-\alpha} dj) \tag{4}$$

(5) $$R(h_1, h_2, k_j) = (1-B)A_j((1-\rho)h_1^{\alpha} + \rho h_2^{\alpha})k_j^{1-\alpha}$$

The random matching process that occurs in the second period translates into uncertainty in first period expected returns for both workers and firms. Because workers don't know either the type or the capital intensity of the firm with which they will match, their expected returns depend on the entire distribution of firm types. Similarly, because firms don't know the skill level of the worker with which they will match, their expected returns depend upon the distribution of worker types. It is this uncertainty coupled with the fact that firms must make their investment decision before meeting a worker that is key to generating endogenous technology in the model. Firms therefore make their investment decision in period one by equating the marginal increase in their expected return of increasing their capital investment to the marginal cost of capital.

(6) $$(1-B)(1-\alpha)A_j k^{-\alpha}((1-\rho)h_1^{\alpha} + \rho h_2^{\alpha}) = \mu$$

This equation can be solved to find a closed form solution to the firm's investment decision.

(7) $$\Rightarrow k = \left(\frac{(1-B)(1-\alpha)A_j}{\mu}\right)^{1/\alpha}((1-\rho)h_1^{\alpha} + \rho h_2^{\alpha})^{1/\alpha}$$

Comparative statics show

(8) $$\frac{\partial k}{\partial A_j} > 0 \qquad \frac{\partial k}{\partial \rho} > 0$$

Therefore, the model suggests two main factors that will effect a firm's investment decision. A_j captures a firm's ex-ante heterogeneity in the model. The higher A_j is the more likely a firm is to heavily invest in capital. Empirically it represents factors such as managerial ability or corporate culture that are inherent, semi-fixed characteristics of the firm. ρ is the proportion of workers in the local labor market that are high skilled. Firms located in more skill intensive areas should, according to the model, invest more in capital. The intuition for this result is simple. A more skilled worker raises the marginal benefit of investing in capital. Therefore if a firm knew with certainty the skill of the worker that it would match to in the second period, the optimal investment for the firm would increase with the skill of the worker. Because the firm doesn't know the type of worker with which it will match, it bases its investment on the expectation of what that worker will be. If there are a large number of highly skilled workers in the local labor market, i.e. a high ρ, the probability that the firm will match with a highly skilled worker increases, and therefore the firm invests more heavily.

Data

Workers

All of the data used in this research are part of the Longitudinal Employer-Household Dynamics program at the Census Bureau. Information on workers comes from the Unemployment Insurance wage records for the selected three states[2]. These files contain person identifiers that allow one to track a worker's earnings within a state over the available period[3]. The data also contain firm identifiers that allows for an exact link between the UI files and other data sets. The UI wage records contain virtually all business employment for the states included in the analysis, creating a final sample size of 198,644,076 observations representing 37,875,250 people and 3,989,740 firms. The disadvantage of using the UI wage data to characterize workers is the limited demographic information available. Within the Census bureau, this problem has been partially overcome by combining the UI wage data with other administrative data containing information on date of birth and gender. Additionally, as will be discussed in more detail in the estimation section, the panel aspect of the data allows one to separate out worker and firm effects.

The local labor market throughout this paper will be defined as county of work for the employees. There is some limited county of residence information also available in the data, however, it only provides best available county of residence for 1999 and forward. Additionally,

[2] Three states were chosen on the basis of time-series availablity at the time of project inception from the set of 18 available states that spanned the time period necessary for this analysis. A list of the full states available and additional information about the LEHD program is available at lehd.dsd.census.gov.
[3] Time periods vary by state, with the latest start date at 1991 and the earliest end date at 1998.

there are many reasons why the county of work is preferable. The local labor market for this model is defined as the region around a firm from which it can draw potential workers. Given that workers have varying preferences for place of work depending upon disutility of commuting and amenities of particular areas, the best assumption for where a worker may potentially be interested in working would be defined by the current place of work rather than the place of residence. One potential drawback to defining local labor market skill by county of work is that by definition it only includes the working portion of the local labor market. This issue of mismeasurement will only cause problems if unemployment rates are large and the distribution of skill among the unemployed varies widely across counties, which seems to be an unlikely problem.

The county is used to define the local labor market, as opposed to the metropolitan area, largely because the measure of the local labor market is defined by where individuals work rather than where they live. The metropolitan area definitions are created to capture a center of economic activity and the surrounding areas from which workers commute. However, because this analysis is based on where individuals work, the metropolitan area definitions are less relevant here. Also, there is statistically significant variation in county skill within metropolitan areas[4]. Given that local labor market skill is the key independent variable, the greater variation will aid in identification of the effect of local labor market skill. Despite the arguments given for using the county of work to define local labor market skill, as a robustness check, metropolitan area skill is also used as a measure of local labor market skill in the investment equation.

As mentioned above, the UI wage records contain identifiers for a worker's firm, but not on a worker's establishment. Without the establishment identifier for each of the workers, it becomes difficult to create a measure of local labor market skill, which is an aggregation of individual worker skills. In particular, if a firm has establishments in multiple counties, it is impossible to determine to which county to assign the worker. While multi-unit firms only represent approximately 30% of employment for the states being studied, some algorithm must be used to allocate these workers to the correct county. Fortunately, the ES202 files provide

[4] See Nestoriak(2003).

additional information that circumvents this problem. In particular, the ES202 lists all the establishments, their county location, and the number of employees at each establishment for all of the firms. From this data set, it is possible to assign each worker to the county in which the firm employs the most workers. While it is impossible to determine which workers are properly assigned, a simple tabulation verifies that 91% of workers are employed in the county in which the firm employs the most workers, therefore this procedure correctly identifies the county of work for 91% of the workers

Investment

Information on establishment investment comes from the 1992 Manufacturing Census. In 1992, and Census years prior to 1992, the manufacturing Census included a series of detailed questions on capital expenditures for the Annual Survey of Manufactures (ASM) sample within the Census. The ASM disproportionately samples large establishments and provides sample weights to make the data representative of all establishments.[5] In addition to the sample weights, the total value of shipments is also used to weight the investment equation results to make the analysis representative of overall economic activity. The key measure of investment here focuses on expenditures on new computer equipment. In order to create a measure of computer investment that can be used in the subsequent analysis, a few transformations of the computer investment data are necessary. The first problem arises because the computer investment data is reported in thousands of dollars spent at each establishment, and it must be standardized across firms of various sizes. A few approaches are taken here. The first is to divide computer investment by total equipment expenditures, to create a measure of the technology bias in investment. The second divides computer investment by total employment at the establishment, to create a measure of computer investment per worker.

The second problem arises because the model has only very limited dynamics, and the data on computer investment is only available in a single year cross section, thereby the estimation implicitly assumes that capital investment is in a non-durable good. There is some

[5] The ASM sample consists of a certainty and a sampled component. The certainty component includes all establishments in companies with greater than $500 million in shipments in 1987, accounting for 18,000 establishments, and all establishments with greater than 250 employees, accounting for 10,000 establishments. The remainder of the

support for this assumption, although deciphering the expected lifecycle of computer equipment is a difficult task. While computer equipment may not be a non-durable good, existing research shows that it has a short life span that seems to grow shorter as time passes. Within the data, the main problem with modeling computers as a non-durable is the treatment of establishments with zero investment in the data. While these establishments may be low technology firms, they may also be firms who invested heavily in the previous period. The information available in the data makes it impossible to distinguish between these two groups, and approximately half of the firms included in the analysis have zero computer investment. The second group of zero investors presents some potentially serious problems for estimation. Two aspects of computer investment argue in favor of a large number of the zeroes being low-technology firms. The first relates to the above discussion on computer depreciation and age of computer retirements. If the average life span of computer equipment is around a year, then there is no problem; the zeroes most likely represent low-tech firms. If the average life span of computer equipment is as long as several years, this problem is more serious, and more of the zeroes are likely to be firms who invested in other periods.

The second aspect of computer investment that argues in favor of the zeroes being low-tech firms is the sharp increase in computer investment by manufacturing establishments between 1982 and 1992. Dunne, Foster, Haltiwanger, and Troske have measured the mean level of computer investment per worker in manufacturing to be \$40 in 1982, \$140 in 1987 and \$830 in 1992. These numbers suggest that not many manufacturing firms had invested heavily in computer equipment in prior years. Additionally, the potential uses of computer equipment in manufacturing is increasing over the time period, so that it is likely that a even a firm that invested in previous periods would have to invest in the current period to truly remain on technology's cutting edge.

In estimating the investment equation, the cross section of data is in essence a mismeasured version of the ideal computer investment measure. As a robustness check to the base estimation that assumes computer investment is nondurable, and therefore the zero

---

27,000 ASM establishments is sampled on the basis of establishment size and industry-level year-to-year volatility in investors are not high technology users, the zero investors are grouped with the small investors. Grouping the firms in this fashion assumes that truly high-technology firms will invest significantly in every time period, but that it is impossible to distinguish between non-investors and small investors using the available cross-sectional data. A probit is then used to determine to what extent county level skill predicts whether firms are high technology firms, and these results are compared with those from the estimation based more directly on the model above.

The link between the data on investments and workers is available at an Employer Identification Number (EIN) level[6]. The EIN is an administrative unit that for a multi-unit business may be broader than an establishment and as large as a firm. For a single unit firm, the EIN is identical to the establishment. Therefore the firm level characteristics calculated using the UI data, firm effect and firm level human capital, are at an EIN level so that they an be matched to the investment data. However, because an EIN can have establishments in multiple counties, the EIN is not an acceptable aggregation level for the firm investment data given that a goal of the analysis is to test the connection between a firm and local labor market skill of the county in which it is located. In order to handle this problem, the investment data is aggregated to an EIN-county level, so that the investment numbers reflect data from all the establishments for a given EIN within a given county. This level of aggregation circumvents the problem of trying to match establishments in the UI data to establishments in the Census data when the common identifier is at an EIN and affects about 5% of the observations.[7] In addition, in the analysis here, the key variable is the skill level of the county, thereby making an establishment level match unnecessary. Throughout the rest of this analysis, the EIN-county unit of aggregation will be referred to as the establishment.

Estimation

---

shipments.

[6] While the EIN is the only common identifier between the two datasets, there are other variables in common between the datasets, such as SIC, employment and payroll, that could be used as an additional restriction on the match. Using additional restrictions, ie requiring that the EIN has the same SIC code in both datasets, has little effect on any of the results.

[7] With computer investment as a percentage of equipment investment as the dependent variable, 6,780 out of 7,155 observations are single establishment ein-county level observations. With computer investment per worker as the dependent variable, 8,336 out of 8,727 observations are single establishment ein-county level observations.

There are two key equations from the model that are estimated using the data described above. The first equation is the ex-post wage equation which, after taking logs of both sides, is

$$\ln W_{ijt} = \ln B + \ln h_i^{\alpha} + \ln A_j k_{jt}^{1-\alpha} \tag{9}$$

Examining this equation, the model suggests that wages are a function of a constant, worker human capital, and firm characteristics. Translating this equation to take advantage of what is available in the data, the actual equation used in estimation is

$$w_{ijt} = \theta_i + X_{it}^{'}\beta + \psi_{j(i,t)s} + \varepsilon_{it} \tag{10}$$

This decomposition of wages is a variation on the methodology developed by Abowd, Kramarz, and Margolis (1999). Wages are measured on an annual basis (see Abowd, Lengermann, McKinney (2003) for details on construction of annual wage measure and the experience measure). Human capital is captured in the fixed worker effect, θ, and a quadratic in experience captured within X. Firm characteristics are captured in the limited time varying firm effect,ψ. The remaining variables contained in X are a series of gender by year by labor force attachment status dummies added to control for assumptions necessary to create an annualized wage measure from the quarterly earnings data. These variables also control for the observable time-varying characteristics.

The firm component of a worker's wages depends upon the firm's fixed type, A_j, and the type of technology being used at the firm, k_{jt}. Potentially, k_{jt} could vary period to period, thereby suggesting fully time-varying firm effects. However, capital investment data is only available in two years, 1992 and 1997[8]. The limited time-varying firm-effect is a compromise between a fixed firm effect and a fully time varying firm effect. While the fixed time effect is not compatible with the theoretical model laid out above, the fully time varying firm effect is identified off of only the observations for a firm within a given year. The limited time-varying firm effect

[8] Investment data are generally only available during Census years. In this paper the 1992 computer investment data and the 1992 and 1997 equipment investment data are used. Computer investment data are not available in 1997.

contains the best attributes of either strategy, it's compatible with the theory and it is identified off of observations from multiple years. The three sub-periods chosen are as follows: 1991 and earlier or the period before the first investment, 1992 through 1996 or the period before the second investment, and 1997 on or the final period.

Identification in the limited time varying firm effect model requires additional restrictions on the other covariates. In particular, one time effect must be suppressed within each separate time sub-period. The time-varying firm effect is generated by creating three separate identifiers for each firm, corresponding to the three different time periods. The three firm effects are identified separately by the observations for that firm within that time period only. Although the firm effects are not generated in a manner which forces them to be correlated over time, analysis of the results from the wage equation show a correlation of approximately 0.7 between firm effects for the same firm across adjacent sub-periods. These results suggest that a component of the firm effect is fixed, and, therefore, that the limited-time varying firm effect is an appropriate compromise between the theory and estimation constraints.

Due to the large sample sizes, the wage equation is estimated separately for each state using the conjugate gradient methodology as explained in Abowd, Creecy, and Margolis (2002). The results are then pooled across the states included in the analysis, properly adjusting the person and firm effects to control for differences in state level mean wages. Identification of the person and firm effects is then determined by applying a grouping algorithm to the pooled state data. A connected group is determined by taking a firm, then pulling all of the employees of that firm, then take all of the firms those employees ever worked at, then pulling all employees at the larger set of firms, and so on. The connectedness of the data is generated by the mobility of workers across firms. Within each connected group all but one person or firm effect is identified. For the group of states included in this analysis, 99.9% of the observations are in one connected group[9]. In practice, the identification restriction is applied by setting the mean of the person and firm effects equal to zero for each connected group.

[9] This group represents 99.1% of all workers and 89.3% of all firms in the pooled three state sample.

The second equation describes investment behavior of firms. Using equation (5) above and taking logs of both sides yields

$$(12)\ \ln k = \ln\left(\frac{(1-B)(1-\alpha)}{\mu}\right)^{1/\alpha} + \ln A_j^{1/\alpha} + \ln((1-\rho)h_1^{\alpha} + \rho h_2^{\alpha})^{1/\alpha}$$

In this equation, log investment is a function of a constant, which itself is a function of parameters of the model, the limited time-varying firm effect, and local labor market skill. Re-writing the equation to make it consistent with earlier notation for the empirical work creates

$$(13) \qquad k_{jt} = \phi_0 + \phi_1 \hat{\psi}_{jt-1} + \phi_2 \hat{s}_{lt-1} + \upsilon_{jt}$$

Taking the components of the model one by one, k_{jt}, the investment variable, has been discussed in the data section, $\hat{\psi}_{jt-1}$, the limited time-varying firm effect, is estimated in the wage equation (8) and $\hat{s}_{lt}$ is one of the measures of labor market skill described above. While the model laid out above doesn't predict what the magnitude of ϕ_2 should be, the model does clearly suggest that ϕ_2 should be positive.

Characterizing human capital

Table 1 summarizes the results of estimating equation 10 with limited time varying firm effects. Looking across the first row, the correlation of log wage with the worker effect is 0.56 and the correlation with the firm effect is 0.50. These results suggest that worker and firm effects are equally important in explaining the variation in log wages. The covariance between the worker and firm effects at the individual level is positive, although small in magnitude at 0.07. The positive covariance between worker and firm effects suggests that high skill workers are more likely to be at employed at high wage firms. The results from estimating the wage equation are then used to quantify worker and firm heterogeneity. For the worker, two measures of human capital are used. The first measure uses only the worker effect, θ_i. The worker fixed effect in this model captures the component of the workers wages that can be attributed to the worker and reflects any fixed characteristic of the worker that affects his wages. Although no individual level comparison of the worker effect and more traditional measures of skill are done in this paper, Abowd, Lengermann, and McKinney(2003) have found that there is a positive correlation between the worker effect and education. The second measure is constructed as follows

$$\hat{s}_{it} = \hat{\theta}_i + \widetilde{X}_{it}\hat{\beta}$$

where θ_i is the fixed worker effect, and $\widetilde{X}$ is the subset of X that contains the quadratic in experience. This second measure of human capital captures returns to experience in addition to the worker effect.

Throughout the rest of the paper it is necessary to use functions of the individual level skill to define either firm or local labor market level skill measures. While the thetas estimated at the individual level are inconsistent, these functions of theta aggregated to the firm or county level are consistent[10]. Two alternative measures of skill are used interchangeably throughout the paper. The first is a simple average of either of the human capital measures within the firm or local labor market, θ_l^{mn}. The second measure calculates the percentage of workers within the firm or local labor market that are above a given threshold of the overall three-state distribution of the human capital measure, $\theta_l^{>75}$, for a given reference year, chosen as 1992. For the calculations here, the threshold chosen is the 75th percentile, and therefore the measures represent the top quartile of worker human capital[11]. These two measures capture different aspects of the skill distribution that are differentially valued by firms. The skill measures created here are also compared with the percentage of college graduates by county below.

---

[10] Abowd, Kramarz, and Margolis (1999) show that for firm level averages of the person affect, $\hat{\theta}_j \equiv \frac{1}{N_j} \sum_{(i,t)\in\{J(i,t)=j\}} \hat{\theta}_i$, using the asymptotic distribution $\hat{\theta}_j \to N(\theta_j, \sigma^2_{\theta_j})$ as $N_j \to \infty$ where N_j is the number of observations for firm j and $\sigma^2_{\theta_j} \equiv \frac{1}{N_j^2} \sum \frac{\sigma^2_\varepsilon}{T_i}$ under the assumption that the distribution of firm sizes is constant.

[11] The 90th percentile was also used in earlier versions of this paper and produced results similar to that of the 75th percentile.

In order to identify the effect of local labor market skill in the investment equation, there must be variation across counties in skill. Figures 1-4 depict county level skill over the time period in a series of kernel density estimates for two different measures of county level human capital. The kernel density estimate is computed using

$$\hat{f}_k = \frac{1}{nh}\sum_{i=1}^{n} K\left(\frac{x - X_i}{h}\right)$$

where n is the number of observations, h is the bandwidth, X_i is the skill measure and K is the Gaussian kernel. Figure 1 consists of a kernel density estimate of the percentage of workers in each county who are in the top quartile of the 1992 theta distribution, $\hat{\theta}_{lt}$, plotted separately for 1991, 1995, and 1998. The shape of the distribution in each of the years appears to be mildly multi-modal with a large number of lower skill counties and a smaller concentration of high skill counties. There also appears to be wide variation in the percentage of workers in each county who are in the top quartile of all workers overall with the least skilled county having 10% of these workers and the most skilled counties having over 30%. Over time the shape of the distribution largely remains constant and the entire density shifts to the right. This shift in the distribution provides evidence that all counties appear to become more skilled over the 1990s. Figure 2 repeats the same measure of county level skill as used in Figure 1, but in Figure 2 each county is weighted by the number of fulltime employees working in the county in 1991. The stark difference in the shape of the densities is due to the large variation in the number of workers across counties. While the median county has just over 10,000 workers, the mean number of workers in a county is around 94,000 with a standard deviation of 378,000. Comparing the unweighted and weighted distributions, it becomes clear that most workers work in highly skilled counties. The general patterns found in the unweighted distribution remain in the weighted distribution. The weighted distribution appears to be mildly bi-modal and is clearly shifting to the right over time.

Figures 3 and 4 repeat the kernel density estimates this time measuring county skill by measuring the mean theta for each county. The distribution in Figure 3 does not appear to be bi-modal but maintains a similar shape with a larger mass in the lower end of the distribution than in the high end. Over time, the distribution appears to be shifting to the right and becoming more concentrated. Looking at the weighted distribution in Figure 4, it appears that the concentration of workers in a few high skill counties is even more prevalent when measuring county skill by mean theta than by the percentage of workers in the top quartile. The weighted distribution has a long left tail and a large peak in the higher skill end repeated across the three years being studied.

The model does not make a clear prediction for converging versus diverging skill across local labor markets. The model would predict that higher human capital counties would have higher wages for all workers, because firms are lead to invest more heavily. This fact alone would not necessarily affect the skill mix of local labor markets, but would lead to higher growth in high human capital areas. Changes in the skill mix within counties would arise, however, if highly skilled individuals were more mobile. In this case, the higher human capital individuals would concentrate close to one another leading to divergence in local labor market skill levels. However, a full analysis of these dynamics will be left for future research.

In order for firms to be able to predict the skill available in the local labor market, there must be persistence in county skill. Figures 5 and 6 study sort term and long term changes in county skill. The clustering of counties around the 45-degree line is, not surprisingly, very tight at the county level. Since these county level skill measures are defined by the individuals' place of work, changes to these measures occur whenever a worker switches both firm and county. Over the shorter time horizon, the overall increase in skill translates into a fitted regression line that is a small parallel shift of the 45-degree line, emphasizing the persistence in variation discovered in earlier figures. Over the longer time horizon, the overall increase in skill results in a fitted regression line that is above the 45 degree line but also slightly less steep. The fact the slope of the fitted line is less than one reinforces the earlier conclusion that when observing the county level skill there is a mild decrease in variation. Despite this small decrease in variation, it is clear that while workers may be mobile, there mobility patterns reinforce the existing distribution of skill across counties, thereby suggesting that establishments are limited to the type of workers found in their local labor market.

Because the measures of skill used throughout this paper are non-standard, it is useful to compare the skill measures computed with LEHD data with more traditional skill measures. In particular, a common proxy for skill is education. In order to compute a county skill level measure analogous to the percentage of workers in the top quartile, the percentage of workers with a college degree is calculated for each county in the LEHD sample using the 100% sample of the long form of the 1990 Decennial Census of Population. While the Census data is only available in 1990, and every ten years, the appropriate county skill measure for the investment equation regressions is the 1991 skill level because investment is measured in 1992. Although the two two county skill measures, percentage of college graduates in 1990 and percentage in the top quartile in 1991, are measured in different units, they have similar means, 0.190 and 0.196 respectively. However, the college graduate measure has a higher variance, 0.062 versus 0.048. The correlation between the two measures is also high, with a correlation coefficient of 0.73. Finally, figure 7 shows a kernel density estimate of the college graduate measure for 1990, the top quartile measure for 1990 using two states (the third is not available in 1990), and the top quartile measure for 1991 using all three states. All three measures have similar shapes to their density, with a large mass in the left tail of the density and a long right tail, although the pattern appears to be most pronounced in the college graduate measure.

While the percentage of college graduates in a county is an attractive measure of county skill because it is clear what is being captured, it is not an ideal measure. The percentage of college graduates is calculated from responses to the long form of the Census and, as with every other survey, is subject to varying response rates by county and respondent error. In addition, the quality of the college attended, the major chosen, and the success of the student in school are not captured in this measure. The worker fixed effect, on the other hand, is a much richer measure of skill. It captures any attribute of a worker that is fixed and that is valued in the labor market, potentially including the aspects of worker skill missed by the college graduate measure. While the exact components of what is encompassed in the worker fixed effect are unobservable, there are small differences between the different measures. Any differences in the results from using these separately calculated measures would be small. Therefore, the usage of the worker effect to measure skill should produce results similar to more traditional skill measures, while capturing a richer definition of worker skill.

Computer Investment

Before moving onto the regression results from the investment equations, a few more comments must be made on the computer investment variables. Figures 8 and 9 graph the cumulative distribution function for the two constructed computer investment measures, computer investment per worker and computer investment as a fraction of total machinery investment respectively.[12] As is clear in both graphs, nearly half of the sample has zero computer investment. In Figure 8, there is a sharp increase in the CDF right after zero, but the graph quickly flattens out and remains flat. In Figure 9, there is also a sharp increase in the CDF immediately after zero followed by a much flatter increase. Another sharp increase exists in the CDF exactly at 1, as a small portion of the establishments had all of their machinery investment in computers.

When considered within a time series perspective, 1992 was a year of strong growth in computer investment. This growth in the use of computer investment around 1992 also helps to argue in favor of the local skill level being exogenous to the firm. While in equilibrium one would expect that an establishment would choose a location, and therefore local labor market skill, suitable for their technology, the development of new technology, here in computers is an exogenous shock. The median age of a manufacturing establishment used in the analysis is 12 years. These firms made their location decisions based on a local labor market skill level that is, for the more than half of establishments, 10 years old, and, more importantly, based on the available technologies at the time of their entry. In 1982, computer investment per worker in manufacturing was less than 1/20th its 1992 level.[13] In order to account for the large increase in computer investment, the set of technology options must have expanded over the time period, or the price of technology fell to a level where more firms found it profitable to use computers. Regardless, when these firms entered the market, they most likely were unable to predict the

[12] While computer investment/machinery investment is, by definition, bounded between zero and one, computer investment per worker has a very long right tail. Therefore, in order to not disclose the maximum of the distribution, the cumulative density graphed here is truncated at $5,000 of computer investment per worker that roughly captures the bottom 99% of the distribution.

growth in skill in their local labor market and the technologies that would be available to them, so that their location decision was exogenous to the investment decision being studied here.

Results

Before turning to the investment equation regressions, table 2 lists the summary statistics for the investment variables and results from the wage equation relevant to the investment analysis. The final sample for the investment analysis is the result of a match between the Annual Survey of Manufacturing sample of the 1992 Manufacturing Economic Census and the UI wage data for the selected three states. The level of aggregation for this sample is EIN-county. Panel B gives an example of the effects of the sample restrictions and weighting on the key independent variable, mean county skill measured as the percentage of workers in a county who are in the overall top quartile of the theta distribution. If one looks at the unweighted sample of counties, the mean county has approximately 20% of its workforce in the top quartile of the theta distribution with a variance of 0.05. Looking at the sample of counties that match to either of the computer investment variables, the mean county skill is much higher at 25%. The mean county skill is higher in the matched sample because, as shown earlier, counties with larger workforces are more skilled. Weighting county skill by the product of the ASM sample weight and the total value of shipments has little effect on either the mean or variance of county skill.

Panel A of table 3 lists the results for the first set of regressions with computer investment per worker as the dependent variable. There are six different specifications each including a different set of covariates. The first is the most basic specification using only covariates that are implied by the theoretical model: county level skill and the firm effect as calculated from the wage equation. The county skill measure used throughout the investment equation regressions omits the effect of the establishment's own employees on local labor market skill.[14] The second specification adds in firm level skill as a control, the third adds in two-digit industry dummies, the fourth includes both firm skill and the industry dummies, and the fifth specification adds state controls. Firm level skill is added to control for the fact that highly skilled firms may already have

---

[13] See Dunne, Foster, Haltiwanger and Troske (2000).
[14] The county skill measure excluding the establishment's contribution is calculated by subtracting the measure of *firm* (sein) skill weighted by the number of workers at that *establishment* (ein-county).

the workforce necessary to fully utilize high tech investment. As highly skilled establishments are likely to be located in highly skilled counties, the inclusion of firm level skill is necessary so that the coefficient on the county measure is not biased. Additionally, including firm level skill allows one to distinguish between the model outlined here and a competing model in which there are no search frictions. In this alternate model, firms would be able to meet a work and then invest in technology leading to a positive coefficient on firm skill and an insignificant coefficient on county skill. Industry controls are necessary because industries locate non-randomly across geography. If highly skilled counties were comprised of industries that are more likely to utilize computers, again the county skill coefficient would be biased upward. Finally, state controls are included to measure the extent to which the results are driven by cross state differences.

The key coefficient of interest is listed first, the percentage of workers in a county who are in the top quartile adjusted for the establishment's contribution. This coefficient is positive and significant in all of the specifications. In order to put an interpretation on the coefficient, the predicted percentage change in the dependent variable due to a one standard deviation increase in county skill is reported in the last row. In the fourth, and most conservative, specification, the regression implies that a one standard deviation increase in county skill leads to a 33% increase in the amount of computer investment per worker. The other two independent variables in the first four specifications are the firm effect from the wage regressions, psi, and firm level skill. Both of these variables are positive and significant in all but the first specification. Additionally, both variables have coefficients smaller in magnitude than county skill.

The final specification examines the effect of the most highly skilled county on the results. The existence of concentrations of establishments in like industries is well known. While the driving force behind these agglomeration economies may very well be their access to a pool of highly skilled labor and, therefore, consistent with the theory laid out above, the success of these agglomeration economies may also be due to a myriad of factors not captured in the model. In order to determine if the results here are driven by a few agglomeration economies existing in highly skilled local labor markets, an interaction term between each of the key coefficients in the model and a dummy variable for the highly skilled county was included in the sixth regression.[15] While the coefficient on county skill is still positive and significant, the magnitude of the coefficient drops, suggesting that the predicted increase in computer investment per worker from one standard deviation increase in county skill to be around 18%. Throughout most of the rest of the results, the interaction with the most highly skilled county is included in order to present a more conservative estimate of the effect of county skill. Whether or not the forces outlined in the model drive the effect of this most highly skilled county on the results, the inclusion of these interaction terms is necessary because the relationship between county skill and establishment investment in computers is non-linear due to this one county. The sensitivity of the results to such nonlinearities are further explored in the next section.

Panel B of table 3 repeats the specifications in panel A replacing the dependent variable with the bias of investment toward computers. The pattern in the results is very similar. The coefficient on county skill excluding the establishment's contribution falls as controls for firm level skill, industry, and state are included. However, while the coefficient on county skill is positive in all of the specifications, it is only significant when controlling for firm level skill or industry separately, but not when both controls are used simultaneously. When the key coefficients in the model are interacted with the most highly skilled county, the effect is also different with computer bias as the dependent variable. Here the nonlinearities appear to be depressing the size of the coefficient on county skill. Once the interaction terms are included the size of the coefficient increases dramatically and is once again significant. In this specification, a one standard deviation increase in county skill is predicted to increase the bias in investment toward computers at the establishment level by over 8%. The other independent variables in the first four specifications are the firm effect, psi, and firm level skill. The coefficient on the firm effect is negative and significant in all of the specifications, which goes against the model predictions, but small in magnitude. The coefficient on firm level skill is positive, significant, and of a greater magnitude than the coefficient on county skill.

[15] The same exercise was performed using the five highest skilled counties producing very similar results.

The two different dependent variables used to test the model, computer investment per worker and the percentage of investment that is in computers, largely lead to the same conclusions as to the effect of county skill on establishment investment. Both dependent variables predict large effects for county skill, which diminish as additional controls are added. The biggest difference between the two specifications is the sensitivity of the results to the most highly skilled county. While including additional interaction terms decreases the explanatory power of county skill in the first set of regressions, it increases the effect of county skill in the second set of regressions. Much of the difference is likely due to the fact that the computer investment bias measure is bounded between zero and one. Regardless of its location, a firm can at most concentrate 100% of its investment in computers. Computer investment per worker on the other hand is unbounded.

Due to the sensitivity of the results to one county, the preferred base specification is the final column of the table, number six, which includes interaction terms with the most highly skilled county. These results suggest that a one standard deviation increase in county skill will lead to an 18% increase in computer investment per worker, or an 8% increase in the bias of investment towards computers. While these results might seem high, a one standard deviation increase in county skill is equivalent to a five-percentage point increase in the number of workers in a county who are in the top quartile of the overall skill distribution. A five percentage point increase in skill, in which the average county has 25% of its workers in the top quartile, would require a significant reallocation of workers. Still, interpreting the results in this manner is helpful to gauge the importance of county skill in an establishment's investment decision. Regardless of the dependent variable being studied, the effect of a firm's own skill mix, industry, and firm type are also important factors in an establishment's investment decision.

Robustness Checks

Nonlinearities

Given that the most highly skilled county greatly influences the coefficient on county skill, table 4 tests further for nonlinearites in county skill and offers a possible explanation. Column one repeats the base specification but includes no interactions with highly skilled counties.

Column two is identical to the final column in the previous table and includes an interaction between the key independent variables in the model and the most highly skilled county. The third column includes interactions with the top 5% of most skilled counties which includes 9 counties. As shown earlier, the inclusion of interactions greatly effects the coefficient on county skill in both Panel A and Panel B, moving the coefficient in opposing directions in the two panels. Concentrating next on column three, one finds that the coefficient on county skill when the regression includes an interaction with the top 5% of counties by skill does not change much. The results therefore suggest that the nonlinearity with highly skilled counties is concentrated in just one county which happens to be the most skilled one.

The most highly skilled county is not an outlier in that its skill level remains far removed from the rest of the distribution. Rather, this one county has both many skilled workers and high levels of computer investment. The final regression in table 3 highlights one potential characteristic of the highly skilled county that may be driving this change in the results. In the fourth specification, the percentage of workers employed in high tech industries, sic 35 and 36[16], is included as a covariate. These results are very similar to the prior regression that included the interaction terms with the most highly skilled county. As mentioned above, the source of the different results for this one county are likely due to aspects of agglomeration economies which are not captured in the endogenous technology model.

Weighting/firm size

The dependent variables used throughout the analysis so far all require use of the Annual Survey of Manufactures to obtain information on expenditures on computers. This sample of the Census of Manufactures is disproportionately large firms and is not representative of all manufacturing industries.[17] In order to make the results representative of the average manufacturing establishment the results must be weighted by the Census ASM sample weight. However, the representative firm in manufacturing is rather small and therefore accounts for only a small fraction of the manufacturing industry's output. Due to this fact, all of the regressions in

[16] SIC 35 and 36 are Industrial and Commercial Machinery and Computer Equipment; and Electronic and Other Electrical Equipment and Components, respectively.
[17] See details in footnote 4.

the earlier tables are weighted by the product of the Census ASM sample weight and the total value of shipments for that establishment in order to make the results representative of a given unit of economic activity.

Table 5 repeats the base specification using three different weighting patterns to highlight the effect of weighting on the key results. In the first column, no weights are used, in the second column the Census ASM weight is used, and in the third column the product of the Census ASM weight and the total value of shipments is used, as is used throughout the rest of the analysis. The effect of weighting on the county skill coefficient is similar for either dependent variable although stronger when looking at computer investment per worker. In the unweighted regression the predicted effect of a one standard deviation increase in county skill on the dependent variable leads to a 2% increase in computer investment per worker. Weighting the same regression by the Census ASM weight makes the effect negative, and weighting by the product of the Census ASM weight and total value of shipments increases the effect to 18%. With computer investment per worker, the same effect is 6% with no weighting, 1% with Census ASM weighting, and 8% with Census ASM and total value of shipments as the weight.

The differences in the effect of county skill on investment across the regressions is most likely due to the differences in the explanatory power of different size firms. The unweighted sample is disproportionately composed of large firms, and the Census ASM weight corrects for that so that the results reflect the representative firm, which is much smaller. Finally, the product of the Census ASM weight and the total value of shipments shifts the emphasis back to larger firms again. Why does the effect of county skill seem to be larger for larger firms? This effect may be driven by a variety of reasons. First, computer investment at the establishment level is measured with less error in larger firms. The ASM is collected in order to publish aggregate statistics about manufacturing. Because any aggregate statistic will largely be driven by larger firms, more effort is focused on collecting data in these large firms. Second, there may be non-linearites in the relationship between county skill and establishment investment in computers. In part, this effect is driven by the fact that larger firms need to hire more workers. Earlier research has shown that in order to get the greatest productivity boost from introducing computers, establishments must integrate computers into much of their operations. Larger establishments with larger operations require more skilled workers in order to integrate computers. In addition, larger establishments invest more per worker than small establishments even when controlling for industry, the firm effect from the wage equation, and firm level skill.

The higher costs of mobility for larger firms also provide support that the positive coefficient on county skill is driven by exogenous differences in skill. Smaller firms wishing to integrate computers into their operations can potentially relocate their establishments to areas in which finding appropriately skilled workers is less costly. Therefore, the skill of the local labor market for small establishments may not be completely exogenous. For larger establishments the costs of relocating their establishments is much greater and would likely offset any reductions in the costs of finding skilled workers. For these firms the skill of the local labor market is more likely to be exogenous, and finding a stronger effect of county skill provides more support to the endogenous technology model.

Alternate skill measures

Table 6 tests the sensitivity of the results to different ways of measuring county skill. Column one repeats the base specification. Column two uses the percentage of workers in a county from the top quartile of the theta distribution by measuring human capital using the sum of the worker fixed effect and the predicted effect of experience from the wage regression. For either dependent variable, the effect of county skill is a bit larger when worker experience is included in the skill measure. The third column uses the mean theta in a county and the fourth column uses the mean of the sum of theta and experience. The results from both of these specifications closely follow the pattern found for the top quartile measures when looking at computer investment per worker. With investment bias towards computers as the dependent variable, the effect of mean county skill is smaller when worker experience is included in the measure of skill.

Finally the fifth column uses the percentage of college graduates in a county calculated using the 1990 Census data. For either dependent variable, these results are remarkably close to that found in the base specification. While the results are a bit larger, this specification does not include a control for firm level skill because it is not possible to compute using Census data. The key difference between the final skill measure and the others is that the final skill measure is calculated using individual's responses about their education from the Census while the other skill measures are derived from a wage regression using administrative data. Additionally, this measure of county skill is uses 1990 data while the other county skill measures all use 1991 data. While the results the differences between the results using the employer employee matched data from LEHD and the Decennial Census data may be small, the matched data is necessary for two primary reasons. The first is that the magnitude of the results are deceptively large when using the Decennial Census measure because one cannot control for firm level skill using the Decennial data. The second reason is that firm effect is computed from the matched data and is a control in the investment equation mandated by the model.

The small differences in the predicted change in the dependent variable due to a one standard deviation increase in the county skill measure across the five specifications provides support that the effect being found is not the result of a particular way of measuring skill. The results in the final column are the strongest support for this claim, given that they are calculated in a different way, from a different data source.

Alternate local labor market measure

County of work has been used as the measure of the local labor market throughout the analysis. While a county is a desirable measure of the local labor market for the reasons listed above, the metropolitan area is also commonly used to define a local labor market. Table 7 includes a comparison between the base specification, in column 1, and one in which the local labor market is defined by the metropolitan area[18] in column 2. Because the metropolitan areas are not exhaustive, the counties outside of any metropolitan area are included in one pooled non-metro area group in column 2. Columns 3 and 4 exclude establishments in these non-metro areas. Using either dependent variable and whether or not the non-metro areas are included, the results are largely the same across all of the specifications. With computer investment per

[18] The metropolitan area used in this analysis is either the Metropolitan Statistical Area or the Primary Metropolitan Statistical Area of a Consolidated Metropolitan Statistical Area. For the states included here, there are 40 metropolitan areas.

worker, the results are a bit stronger when using the metropolitan areas especially when the non-metro areas are dropped from the analysis. In panel B, the results with computer investment over machinery investment are a bit larger when the metropolitan areas are used but become a bit smaller when the non-metro areas are excluded from the analysis. The effect of a one standard deviation increase in local labor market skill is a bit misleading because there is less variance in metropolitan area skill than there is in county skill. Regardless, using the metropolitan area as the measure of the local labor market produces results very similar to those produced using county as the local labor market measure.

Probit

As mentioned above, the computer investment data used for this analysis is a cross section. Implicitly, the estimation assumes that computer investment is a non-durable. As a robustness check to the base assumption, establishments are placed into a low investor and a high investor group, where the high investors are in the top quartile of either computer investment per worker or computer investment over machinery investment. Table 8 repeats the base specification, excluding firm skill in column one and with firm skill in column two, and shows the results of the probit, without firm skill in column three and with firm skill in column four. The probit predicts that a one standard deviation increase in county skill will increase the likelihood that a firm is high tech, as measured using computer investment per worker, by 3 to 12% depending on whether or not firm skill is included. While the results in columns one and two appear larger, the specifications are measuring different things and are impossible to directly compare. However, they do both suggest that county skill plays a role in computer investment. In Panel B, the base specification predicts between an 8 and 16% increase in computer investment over machinery investment from a one standard deviation increase in county skill, while the probit predicts between an 18 and 27% increase in the likelihood that a firm is high-tech.

Alternate dependent variables

As a final robustness check, machinery investment per worker, a variable measured independently from computer investment, is used as the dependent variable in table 9. Machinery investment per worker is asked of all establishments in Census years, therefore the results using machinery investment per worker are computed for both years for which human capital data is also available, 1992 and 1997. Because machinery investment data is collected for all establishments, the Census ASM sample weight does not apply here, and results are weighted only by the total value of shipments for that establishment. The results in Panel A, machinery investment per worker in 1992, and in Panel B, machinery investment per worker in 1997, both follow the same broad pattern. The first specification uses theta as the measure of county skill. The second also uses theta and additionally includes interactions between the key coefficients and the most skilled county. The third uses the sum of theta and worker experience to measure county skill and the fourth adds in interactions with the most skilled county. Contrary to the earlier results using computer investment as the dependent variable, the coefficient on county skill is negative in the first two specifications of either panel suggesting that firms in high theta counties are less likely to invest in machinery. However, the coefficient is positive and significant in the last two specifications in which county skill is measured using the sum of theta and worker experience. The difference in the pattern in these results compared to the earlier results using computer investment is likely due to the fact that machinery investment is very heterogeneous. While machinery investment includes computer investment, it is also comprised of much older technologies. These older technologies are likely to disproportionately require worker experience.

The other key difference between these results and the computer investment results is that because machinery investment is not necessarily a new technology, it is difficult to argue that the skill of the local labor market is exogenous to the establishment's investment decisions. Establishments who choose a high capital intensity/highly experienced worker strategy may well have made that decision at the time that they made their location decision. Therefore, the skill of the local labor force may be driving the location decision of firms in regards to their machinery investment patterns. While these arguments can explain the difference in the results across the different dependent variables, it is more difficult to explain why the coefficient on county skill measured as the sum of theta and worker experience is higher using machinery investment in 1992 versus 1997. Machinery investment per worker is much higher in 1997, with the median establishment investing approximately $6,700 per worker while in 1992 the median establishment invested approximately $3,700 per worker. Part of the difference between the results is that in the top panel the predicted 11% increase in the dependent variable is measure off of a lower mean that the 2% increase predicted in the bottom panel. Still, regardless of the difference in the level of machinery investment in the two years, the regression predicts that a one standard deviation increase in county skill will lead to a $1,405 increase in machinery investment in 1992 and a $310 increase in 1997. While the endogenous technology model does not fit as well using machinery investment per worker as the dependent variable, table 8 provides some evidence that the results laid out in the earlier tables using computer investment are not a strange artifact of the computer investment data.

Conclusion

There is tremendous heterogeneity in the technology employed by firms, even in well-defined industries. One potential cause of this heterogeneity is endogenous technology driven by the variation and persistence of human capital across different local labor markets. The research here builds a matching model capturing the effects of local labor market worker skill on establishment investment decisions. By taking advantage of a unique employer-employee matched dataset, the results begin to quantify the effects of local labor market skill on establishment technology.

The best estimates of the effect of county skill on an establishment's investment predicts that a one standard deviation increase in county skill will lead to an 18% increase in computer investment per worker and an 8% increase in investment bias toward computers for a representative unit of economic activity. Weighting the results and thereby shifting the emphasis between smaller and larger firms does affect the results. The affect of an increase in county skill is not nearly as large for a representative establishment. This outcome is likely due to the fact that county skill has a greater impact on the investment decisions of larger firms. However, the results are robust to different ways of measuring county skill and different functional forms of the specification. These results are also not unique to computer investment in 1992. When county level skill is measured by including the effect of worker experience, one finds similar results with machinery investment per worker as the dependent variable. The pattern found in the results is consistent with other research on technology adoption. Productivity enhancements from the usage of computers require widespread changes in an establishment. These changes require a large investment in skilled workers. The research here suggests that firms are more willing to make the investment in computers if the necessary workforce is available.

One area for further research is to explore how endogenous technology affects the dynamics of worker location. While the empirical work here uses investment in computers in a relatively early time period to ensure that workers are exogenously distributed in reference to firms' likelihood of investing in computers, data in later periods can be used to examine workers reactions to firms' investments. The results here suggest that it is in the best interest of the high-tech firm and the highly skilled worker to locate in high skill areas. As the usage of technology has increased in the area does one also see an increase in the concentration of skilled workers?

Table 1: Correlations between wage regression coefficients

	Log wage	Worker effect	Firm effect	XBeta	Residual
Log wage	1	0.5643	0.4958	0.2294	0.4207
Worker effect		1	0.0655	-0.4740	0.0000
Firm effect			1	0.0355	0.0000
XBeta				1	0.0000
Residual					1

Wage regression computed separately for three states and pooled, adjusting for state means. The final sample size includes 198,644,076 observations representing 37,875,250 people and 3,989,740 firms. (I'm assuming that the sample size numbers are enough information for disclosure.)

Figure 1

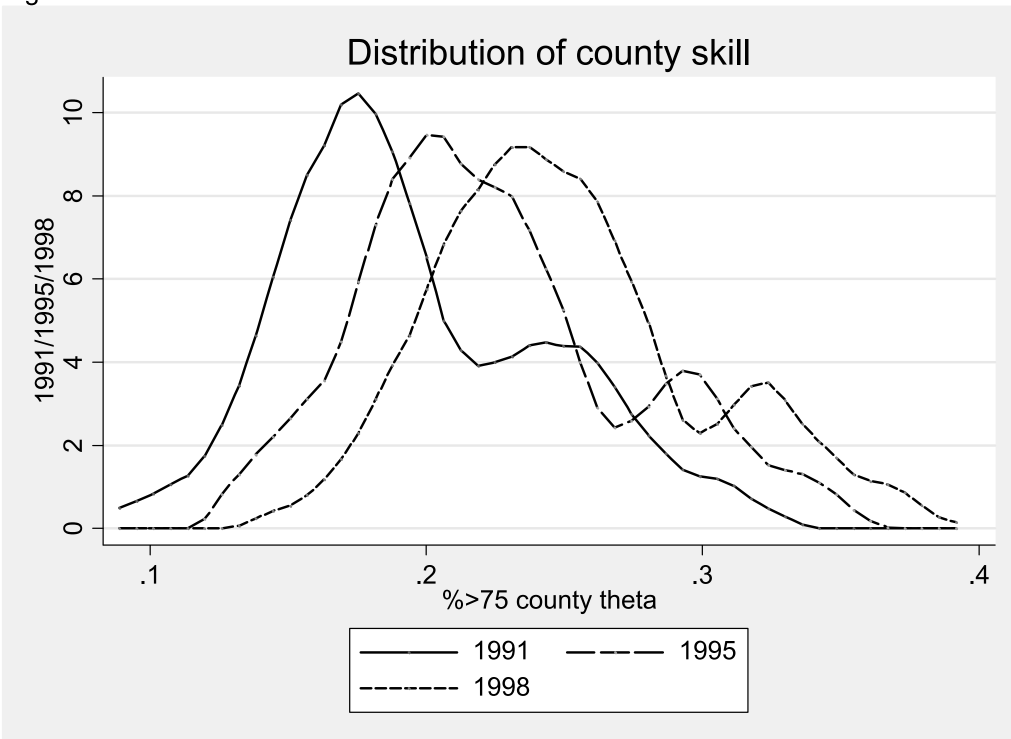

Figure 2

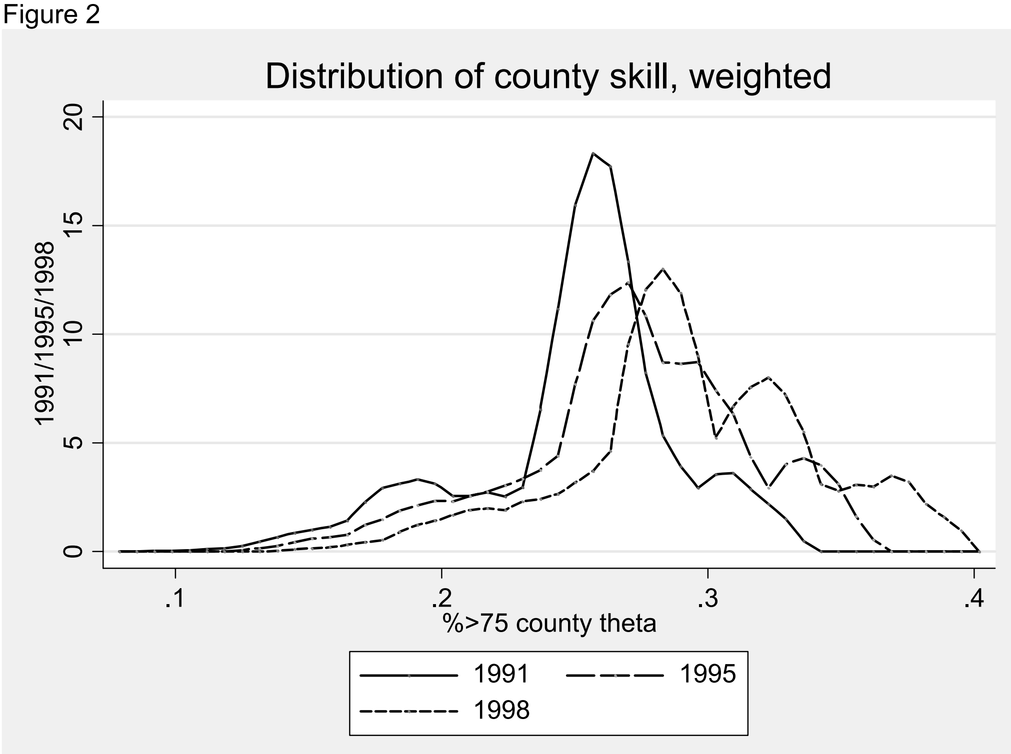

Figure 3

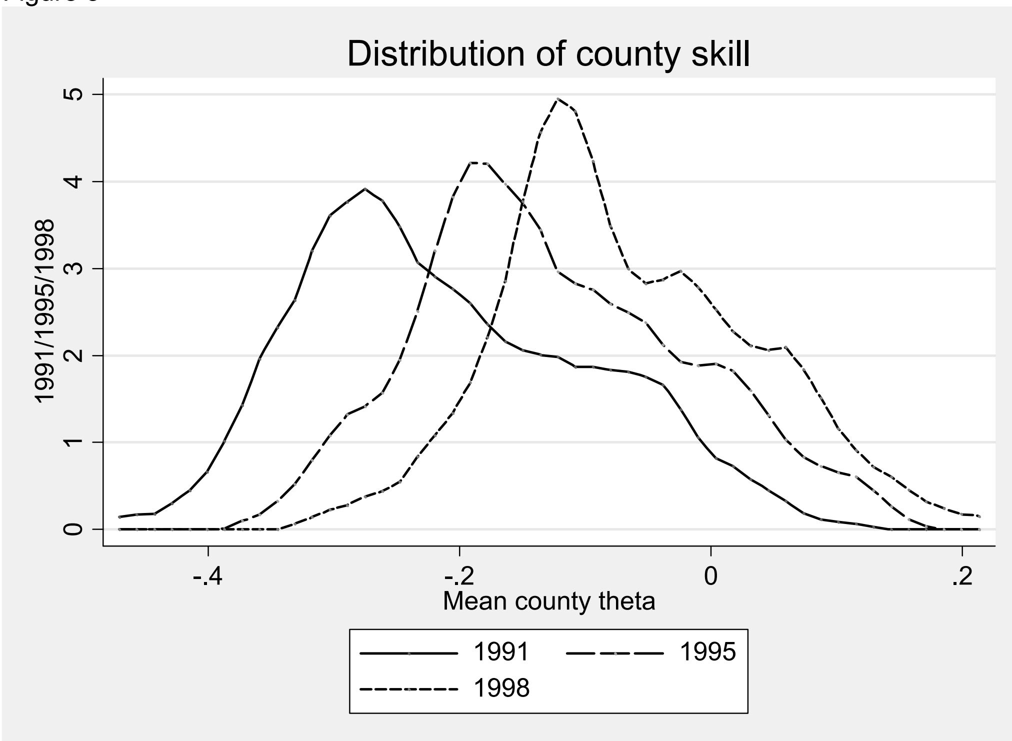

Figure 4

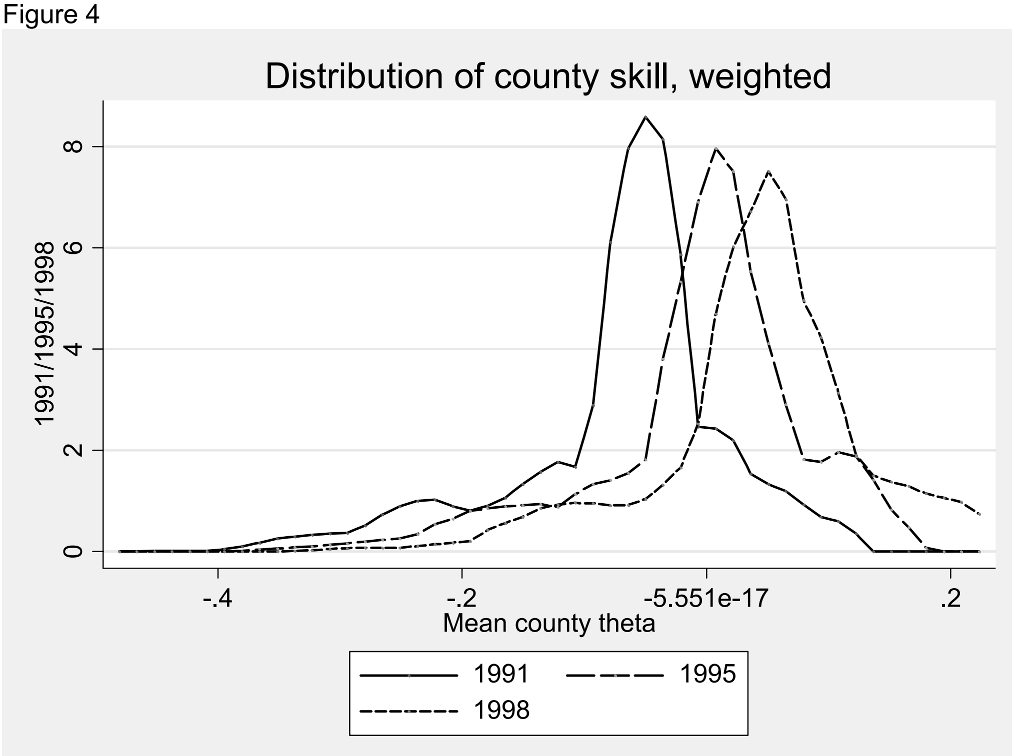

Figure 5

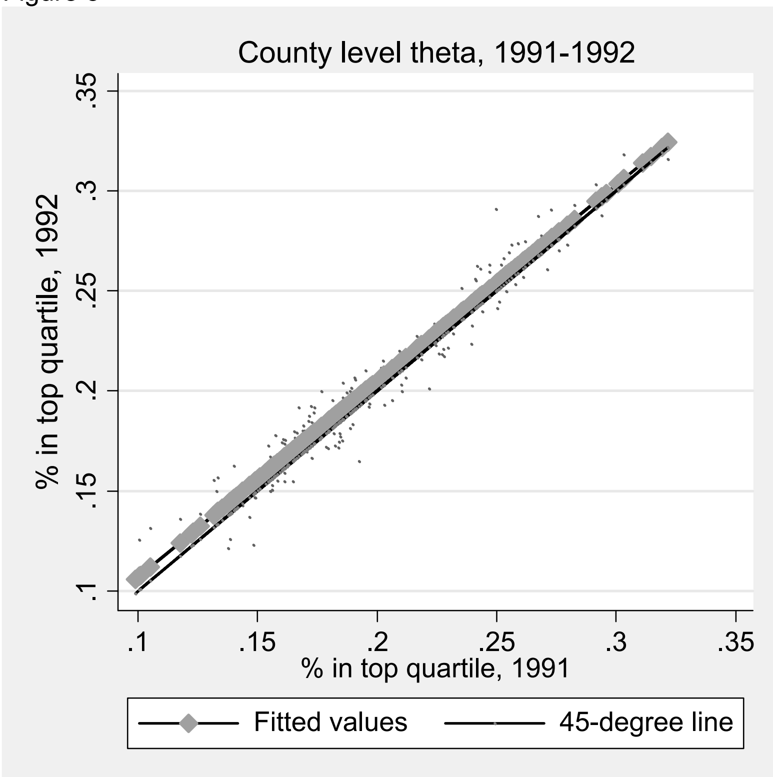

Figure 6

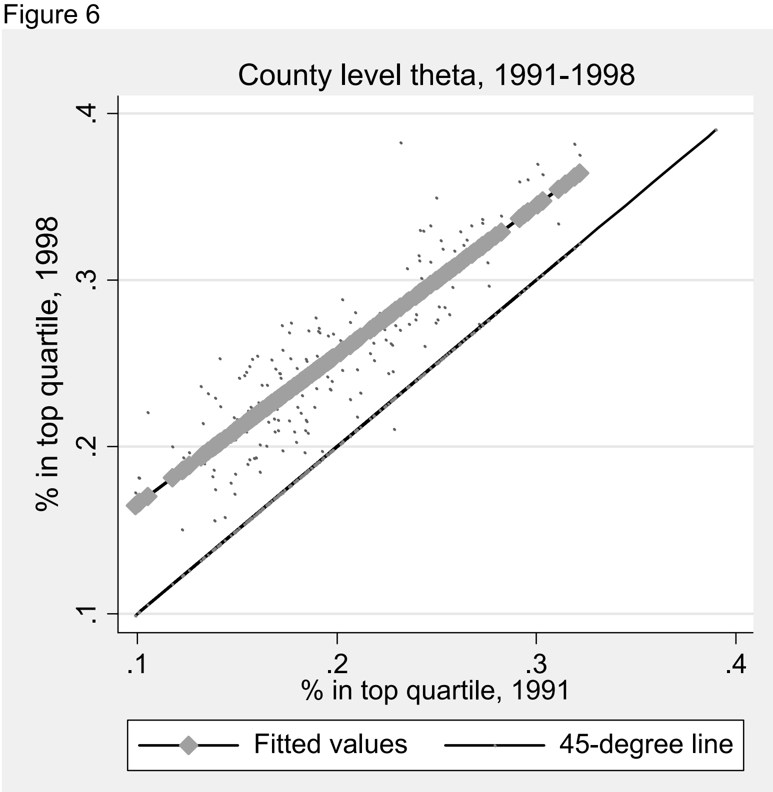

Figure 7

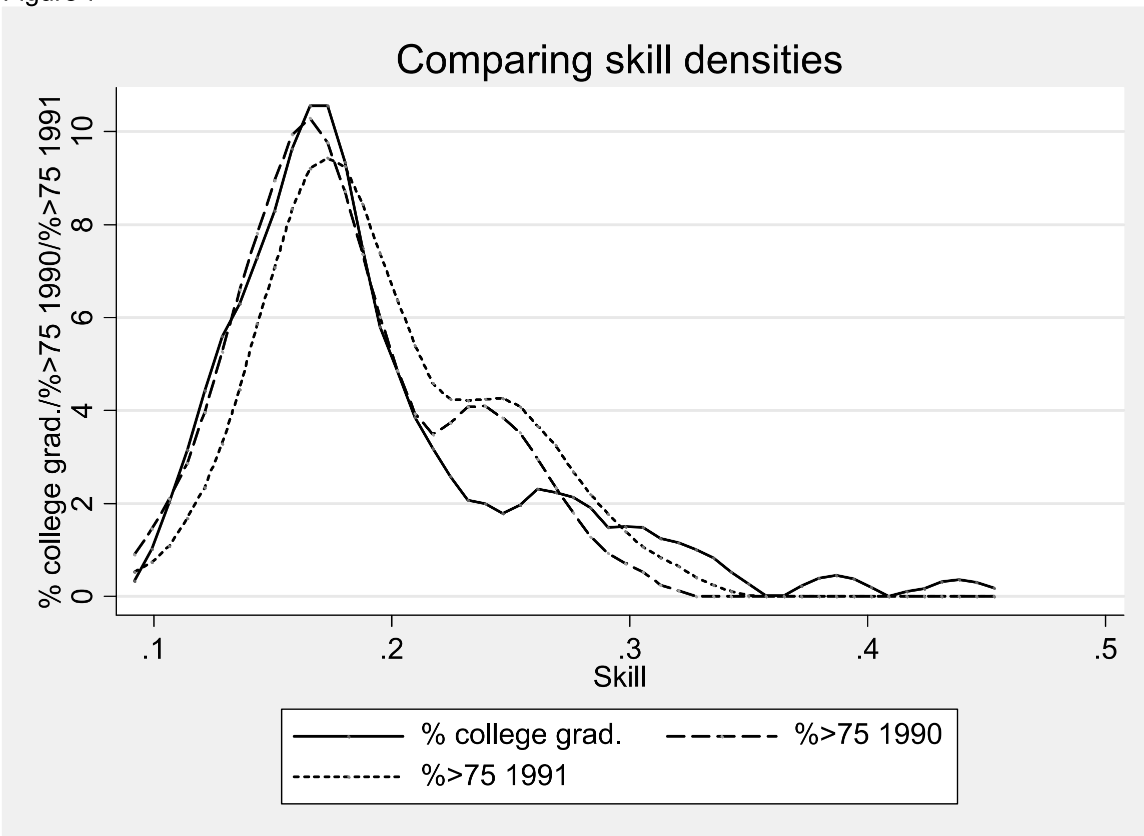
Comparing skill densities
% college grad./%>75 1990/%>75 1991
0
2
4
6
8
10
.1
.2
.3
.4
.5
Skill
% college grad.
%>75 1990
%>75 1991

Figure 8

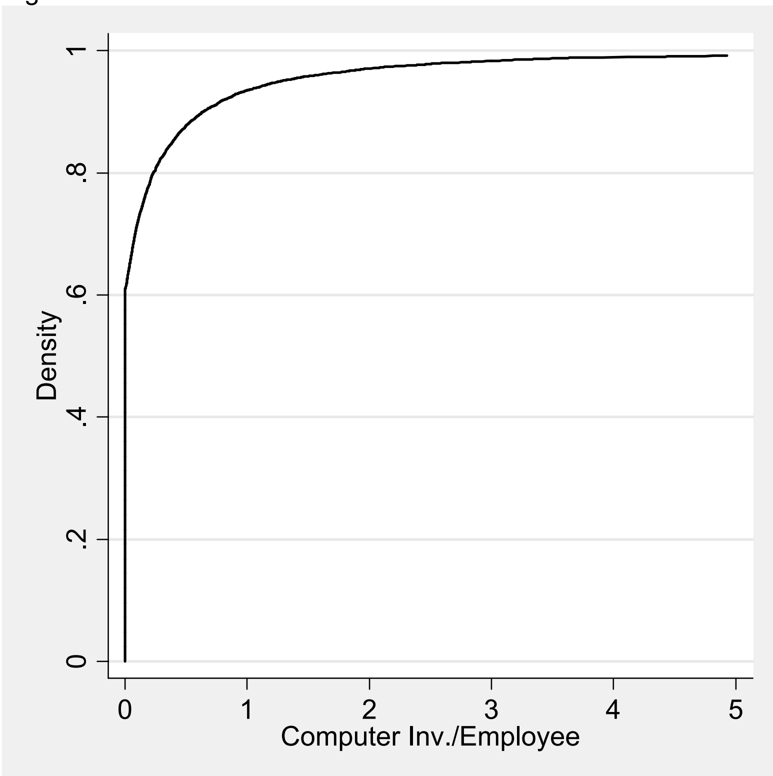

Figure 9

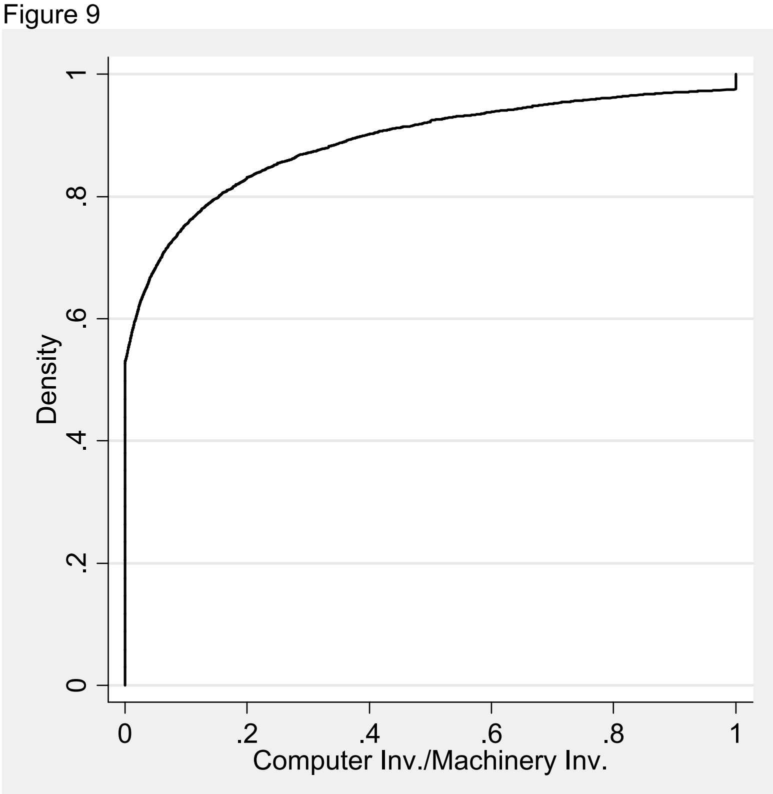

Table 2: Summary Statistics

Panel A

	Data sample	Number of obs.	Mean	Standard Deviation
Computer Inv. per worker ($1000)	1992 ASM X UI Wage	8339	0.2819	1.4539
Computer Inv. per worker ($1000, weighted)	1992 ASM X UI Wage	8339	0.7313	1.6881
Computer Inv. /Machinery Inv.	1992 ASM X UI Wage	6835	0.1110	0.2272
Computer Inv. /Machinery Inv. (weighted)	1992 ASM X UI Wage	6835	0.1261	0.1802
1991 county skill, $\theta_l^{>75}$	UI Wage	184	0.1957	0.0476
1991 county skill, θ_l^{mn}	UI Wage	184	-0.2096	0.1143
1991 estimated firm effect, ψ	UI Wage	916,896	-0.0138	0.7579
1991 firm skill, $\theta_j^{>75}$	UI Wage	916,896	0.2268	0.2943
1991 firm skill, θ_j^{mn}	UI Wage	916,896	-0.1131	0.6473

Panel B

1991 county skill, $\theta_l^{>75}$	UI Wage	184	0.1957	0.0476
1991 county skill, $\theta_l^{>75}$ (matched CI/MI sample)	UI Wage X 1992 ASM	6835	0.2471	0.0407
1991 county skill, $\theta_l^{>75}$ (weighted, matched CI/MI sample)	UI Wage X 1992 ASM	6835	0.2497	0.0399
1991 county skill, $\theta_l^{>75}$ (matched CI/EMP sample)	UI Wage X 1992 ASM	8339	0.2478	0.0400
1991 county skill, $\theta_l^{>75}$ (weighted, matched CI/EMP sample)	UI Wage X 1992 ASM	8339	0.2498	0.0397

Table 3: Results

Panel A: Computer Investment per Worker

	(1)	(2)	(3)	(4)	(5)	(6)
1991 county skill, $\theta_l^{>75}$	9.519** (0.466)	5.442** (0.459)	7.020** (0.471)	5.051** (0.469)	5.840** (0.468)	2.821** (0.513)
1991 estimated firm effect, ψ	0.133 (0.083)	0.467** (0.079)	0.400** (0.089)	0.592** (0.088)	0.822** (0.088)	0.369** (0.085)
1991 firm skill, $\theta_j^{>75}$		3.754** (0.118)		3.009** (0.145)	3.304** (0.145)	2.218** (0.144)
Constant	-1.709** (0.119)	-1.648** (0.112)	-1.341** (0.118)	-1.471** (0.115)	-1.924** (0.127)	-0.722** (0.125)
Observations	8339	8339	8339	8339	8339	8339
R-squared	0.05	0.15	0.15	0.19	0.21	0.25
Ind. controls	no	no	yes	yes	yes	yes
State controls	no	no	no	no	yes	no
Cty interaction	no	no	no	no	no	yes
% osd	61.96	35.43	45.70	32.88	38.02	18.37

Panel B: Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)	(5)	(6)
1991 county skill, $\theta_l^{>75}$	0.838** (0.055)	0.303** (0.053)	0.278** (0.053)	0.054 (0.052)	0.046 (0.053)	0.219** (0.059)
1991 estimated firm effect, ψ	-0.084** (0.010)	-0.037** (0.009)	-0.048** (0.010)	-0.026* (0.010)	-0.028** (0.010)	-0.026** (0.010)
1991 firm skill, $\theta_j^{>75}$		0.484** (0.014)		0.337** (0.016)	0.335** (0.016)	0.325** (0.017)
Constant	-0.047** (0.014)	-0.040** (0.013)	-0.000 (0.013)	-0.015 (0.013)	-0.011 (0.014)	-0.049** (0.014)
Observations	6835	6835	6835	6835	6835	6835
R-squared	0.04	0.19	0.23	0.27	0.27	0.28
Ind. controls	no	no	yes	yes	yes	yes
State controls	no	no	no	no	yes	no
Cty interaction	no	no	no	no	no	yes
% osd	31.63	11.43	10.49	2.05	1.75	8.27

Standard errors in parentheses. Weighted by ASM sample weight and total value of shipments. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 4: Robustness: Nonlinearities

Panel A: Computer Investment per Worker

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	5.051**	2.821**	3.377**	3.739**
	(0.469)	(0.513)	(0.556)	(0.486)
1991 estimated firm effect, ψ	0.592**	0.369**	0.343**	0.586**
	(0.088)	(0.085)	(0.088)	(0.087)
1991 firm skill, $\theta_j^{>75}$	3.009**	2.218**	2.117**	3.060**
	(0.145)	(0.144)	(0.149)	(0.145)
% workers in high skill ind.				3.816**
				(0.400)
Constant	-1.471**	-0.722**	-0.819**	-1.315**
	(0.115)	(0.125)	(0.132)	(0.116)
Observations	8339	8339	8339	8339
R-squared	0.19	0.25	0.23	0.20
County interactions	none	top 1	top 5%	none
% osd	32.88	18.37	21.98	24.34

Panel B: Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	0.054	0.219**	0.220**	0.152**
	(0.052)	(0.059)	(0.064)	(0.054)
1991 estimated firm effect, ψ	-0.026*	-0.026**	-0.027*	-0.026*
	(0.010)	(0.010)	(0.010)	(0.010)
1991 firm skill, $\theta_j^{>75}$	0.337**	0.325**	0.329**	0.332**
	(0.016)	(0.017)	(0.017)	(0.016)
% workers in high skill ind.				-0.283**
				(0.045)
Constant	-0.015	-0.049**	-0.049**	-0.026*
	(0.013)	(0.014)	(0.015)	(0.013)
Observations	6835	6835	6835	6835
R-squared	0.27	0.28	0.27	0.28
Cty interactions	none	top 1	top 5%	none
% osd	2.05	8.27	8.32	5.76

Standard errors in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 5: Robustness: Weight/Firm Size

Panel A: Computer Investment per Worker

	(1)	(2)	(3)
1991 county skill, $\theta_l^{>75}$	0.317	-0.534	2.821**
	(0.443)	(0.299)	(0.513)
1991 estimated firm effect, ψ	0.173**	0.125**	0.369**
	(0.059)	(0.037)	(0.085)
1991 firm skill, $\theta_j^{>75}$	0.992**	0.568**	2.218**
	(0.127)	(0.079)	(0.144)
Constant	-0.095	0.148	-0.722**
	(0.113)	(0.081)	(0.125)
Observations	8339	8339	8339
R-squared	0.04	0.04	0.25
Weight	none	Census	Census*TVS
% osd	2.06	-3.48	18.37

Panel B: Computer Investment/Machinery Investment

	(1)	(2)	(3)
1991 county skill, $\theta_l^{>75}$	0.152*	0.023	0.219**
	(0.075)	(0.082)	(0.059)
1991 estimated firm effect, ψ	0.016	0.058**	-0.026**
	(0.011)	(0.011)	(0.010)
1991 firm skill, $\theta_j^{>75}$	0.087**	0.120**	0.325**
	(0.023)	(0.023)	(0.017)
Constant	-0.004	0.036	-0.049**
	(0.019)	(0.022)	(0.014)
Observations	6835	6835	6835
R-squared	0.06	0.05	0.28
Weight	none	Census	Census*TVS
% osd	5.73	0.87	8.27

Standard errors in parentheses. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 6: Robustness: Alternative skill measures

Panel A: Computer Investment per Worker

	(1)	(2)	(3)	(4)	(5)
1991 county skill, $\theta_l^{>75}$	2.821**				
	(0.513)				
1991 county skill, $s_l^{>75}$		3.670**			
		(0.635)			
1991 county skill, θ_l^{mn}			0.602**		
			(0.230)		
1991 county skill, s_l^{mn}				2.975**	
				(0.305)	
% College Grad					3.486**
					(0.321)
Observations	8339	8339	8339	8339	8339
R-squared	0.25	0.27	0.24	0.25	0.23
% osd	18.37	20.69	9.42	32.33	29.88

Panel B: Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)	(5)
1991 county skill, $\theta_l^{>75}$	0.219**				
	(0.059)				
1991 county skill, $s_l^{>75}$		0.402**			
		(0.077)			
1991 county skill, θ_l^{mn}			0.106**		
			(0.027)		
1991 county skill, s_l^{mn}				0.085*	
				(0.036)	
% College Grad					0.271**
					(0.038)
Observations	6835	6835	6835	6835	6835
R-squared	0.28	0.24	0.26	0.25	0.24
% osd	8.27	13.16	9.58	5.35	13.46

Standard errors in parentheses. Two digit industry dummies, a constant term, and interactions with high skill county are included all the specifications. Firm level skill is included in the first four specifications. Weighted by ASM sample weight and total value of shipments. % college graduates in county calculated from 1990 Census data. County skill measure excludes establishment's contribution in columns 1-4. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 7: Robustness: Alternative local labor market measure

Panel A: Computer Investment per Worker

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	2.821**		3.522**	
	(0.513)		(0.617)	
1991 msa skill, $\theta_m^{>75}$		3.858**		4.881**
		(0.542)		(0.645)
1991 estimated firm effect, ψ	0.369**	0.365**	0.396**	0.402**
	(0.085)	(0.085)	(0.093)	(0.093)
1991 firm skill, $\theta_j^{>75}$	2.218**	2.191**	2.183**	2.173**
	(0.144)	(0.144)	(0.152)	(0.151)
Constant	-0.722**	-0.959**	-0.898**	-1.224**
	(0.125)	(0.132)	(0.154)	(0.162)
Observations	8339	8339	7757	7757
R-squared	0.25	0.25	0.25	0.25
Non-metro areas included	yes	yes	no	no
% osd	18.37	20.00	22.93	25.30

Panel B: Computer Investment/Machinery Investment

	(1)	(2)	(3)	(4)
1991 county skill, $\theta_l^{>75}$	0.219**		0.218**	
	(0.059)		(0.070)	
1991 msa skill, $\theta_m^{>75}$		0.223**		0.208**
		(0.063)		(0.074)
1991 estimated firm effect, ψ	-0.026**	-0.026*	-0.031**	-0.030**
	(0.010)	(0.010)	(0.011)	(0.011)
1991 firm skill, $\theta_j^{>75}$	0.325**	0.326**	0.316**	0.318**
	(0.017)	(0.017)	(0.017)	(0.017)
Constant	-0.049**	-0.051**	-0.045*	-0.044*
	(0.014)	(0.015)	(0.018)	(0.019)
Observations	6835	6835	6326	6326
R-squared	0.28	0.28	0.28	0.28
Non-metro areas included	yes	yes	no	no
% osd	8.27	6.70	8.21	6.25

Standard errors in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County and MSA skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 8: Robustness: Probit

Panel A: Computer Investment per Worker

	(1) ols	(2) ols	(3) probit	(4) probit
1991 county skill, $\theta_l^{>75}$	4.146**	2.821**	1.002**	0.279
	(0.533)	(0.513)	(0.182)	(0.186)
1991 estimated firm effect, ψ	0.312**	0.369**	0.373**	0.444**
	(0.090)	(0.085)	(0.031)	(0.032)
1991 firm skill, $\theta_j^{>75}$		2.218**		1.172**
		(0.144)		(0.061)
Constant	-0.654**	-0.722**		
	(0.132)	(0.125)		
Observations	8339	8339	8338	8338
R-squared	0.16	0.25		
% osd	26.99	18.37	11.96	3.34

Panel B: Computer Investment/Machinery Investment

	(1) ols	(2) ols	(3) probit	(4) probit
1991 county skill, $\theta_l^{>75}$	0.432**	0.219**	2.055**	1.374**
	(0.060)	(0.059)	(0.208)	(0.215)
1991 estimated firm effect, ψ	-0.046**	-0.026**	-0.079*	-0.027
	(0.010)	(0.010)	(0.034)	(0.035)
1991 firm skill, $\theta_j^{>75}$		0.325**		1.070**
		(0.017)		(0.060)
Constant	-0.036*	-0.049**		
	(0.015)	(0.014)		
Observations	6835	6835	6834	6834
R-squared	0.23	0.28		
% osd	16.31	8.27	26.67	17.74

Standard errors in parentheses. Weighted by ASM sample weight and total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

Table 9: Robustness: Machinery investment per worker

Panel A: Machinery Investment per Worker, 1992

	(1)	(2)	(3)	(4)
1991 estimated firm effect, ψ	11.099**	11.422**	9.934**	10.546**
	(0.361)	(0.370)	(0.361)	(0.369)
1991 county skill, $\theta_l^{>75}$	-4.284	-6.152*		
	(2.235)	(2.507)		
1991 firm skill, $\theta_j^{>75}$	16.583**	15.520**		
	(0.680)	(0.721)		
1991 county skill, $s_l^{>75}$			24.047**	29.898**
			(2.461)	(3.124)
1991 firm skill, $s_j^{>75}$			4.645**	4.646**
			(0.673)	(0.709)
Constant	3.531**	4.017**	-0.514	-2.028**
	(0.543)	(0.609)	(0.568)	(0.720)
Observations	56563	56563	56563	56563
R-squared	0.37	0.38	0.37	0.37
% osd	-1.88	-2.69	9.12	11.34

Panel B: Machinery Investment per Worker, 1997

	(1)	(2)	(3)	(4)
1996 estimated firm effect, ψ	21.307**	21.126**	19.825**	19.557**
	(0.415)	(0.423)	(0.426)	(0.435)
1996 county skill, $\theta_l^{>75}$	-12.988**	-16.042**		
	(2.388)	(2.642)		
1996 firm skill, $\theta_j^{>75}$	19.713**	24.481**		
	(0.694)	(0.797)		
1996 county skill, $s_l^{>75}$			5.639*	6.484*
			(2.254)	(2.619)
1996 firm skill, $s_j^{>75}$			14.814**	16.597**
			(0.607)	(0.655)
Constant	10.450**	10.179**	5.779**	5.052**
	(0.639)	(0.709)	(0.679)	(0.785)
Observations	55604	55604	55604	55604
R-squared	0.25	0.25	0.25	0.25
% osd	-4.13	-5.11	1.55	1.79

Standard errors in parentheses. Weighted by total value of shipments. Two digit industry dummies and interaction terms with high skill county included. County skill measure excludes establishment's contribution. % osd is the predicted percent change in the dependent variable due to a one standard deviation increase in county skill.
* significant at 5%; ** significant at 1%

References

Abowd, John M., Robert H. Creecy and Francis Kramarz (2002). “Computing Person and Firm Effects Using Linked Longitudinal Employer-Employee Data.” LEHD Technical Paper 2002-6 (March).

Abowd, John M., John Haltiwanger, Julia Lane and Kristen Sandusky. (2001) “Within and Between Changes in Human Capital, Technology, and Productivity.” (October).

Abowd, John M., Francis Kramarz, and David Margolis (1999). “High Wage Workers and High Wage Firms.” *Econometrica* (March), pp. 251-334.

Abowd, John M., Paul Lengermann, and Kevin McKinney (2003). “The Measurement of Human Capital in the U.S. Economy.” LEHD Technical Paper (March)

Acemoglu, Daron. (1996) “A Microfoundation For Social Increasing Returns in Human Capital Accumulation.” *Quarterly Journal of Economics* (August, vol. 111), pp779-804.

Acemoglu, Daron. (1998) “Why Do New Technologies Complement Skills? Directed Technical Change and Wage Inequality.” *Quarterly Journal of Economics* (November, vol. 113), pp. 1055-1089.

Acemoglu, Daron. (1999) “Changes in Unemployment and Wage Inequality: An Alternative Theory and Some Evidence.” *American Economic Review* (December, vol 89), pp. 1259-1278.

Albrecht, James and Susan Vroman. (2002) “A Matching Model with Endogenous Skill Requirements.” *International Economic Review* (February, 43(1)) pp. 283-305

Bresnahan, Timothy F., Erik Brynjolfsson and Lorin M. Hitt. (2002) “Information Technology, Workplace Organization, and the Demand for Skilled Labor: Firm-Level Evidence.” *Quarterly Journal of Economics* 117(1), pp. 339-376.

Dunne, Timothy, John Haltiwanger, Lucia Foster, and Kenneth Troske. (2000) “Wage and Productivity Dispersion in U.S. Manufacturing: The Role of Computer Investment.” NBER Working Paper No. 7465 (January).

Eudey, Gwen and Miguel Molico. (2001) “Production Synergies, Technology Adoption, Unemployment, and Wages.” Finance and Economics Discussion Series, Federal Reserve Board (July).

Fallick, Bruce C., Charles A. Fleischman, and James B. Rebitzer. (2003) “Job-hopping in Silicon Valley: The Micro-foundations of a High Technology Cluster.” NBER Personnel Economics Summer Institute (July).

Goldin, Claudia and Lawrence F. Katz. (1998) “The Origins of Technology-Skill Complementarity.” *Quarterly Journal of Economics* 113(3), pp. 693-732.

Haltiwanger, John, Julia Lane, and James Spletzer. (2000) “Wages, Productivity, and the Dynamic Interaction of Businesses and Workers.” NBER Working Paper No. 7994 (November).

Kiley, Michael. (1999) “The Supply of Skilled Labor and Skill-Biased Technological Progress.” *Economic Journal*. 109, pp. 708-724.

Moretti, Enrico. (2002) “Human Capital Spillovers in Manufacturing: Evidence from Plant-level Production Functions.” NBER Working Paper No. 9316 (October).